LUCID science: Advancing learning through human-machine cooperation.

Timothy T. Rogers[1] (ttrogers@wisc.edu) and Charles W. Kalish[2] (cwkalish@wisc.edu)
[1]Department of Psychology, 1202 W. Johnson Street
[2]Department of Educational Psychology, 1025 W. Johnson Street
Madison, WI 53706 USA

Keywords: computational methods, modeling, education, collaboration

Introduction

This symposium presents four collaborative research projects conducted as part of LUCID, a unique cross-disciplinary graduate training program funded by the NSF's National Research Traineeship mechanism. LUCID trains scientists from computational and behavioral disciplines to advance basic and applied research in domains where machines are used to instruct, predict, understand, respond to or learn from human users. Such human-machine interactions have a remarkably broad range of application—in public and private education across the lifespan, industry and information technology, public and private health management, social networking and communication, robotics and human-computer interaction, national security, public policy, and, of course, basic research into the nature of learning, cognition, and intelligent behavior.

The current talks all consider how machine learning, cognitive modeling, and data-science might be integrated to address core questions in human learning and education. How can computational learning models best be leveraged to speed knowledge acquisition and breadth of transfer in educational contexts? How can we efficiently measure perceptual and cognitive structures online or in the lab? How do such structures change with increasing knowledge or expertise? How can cognitive models developed to explain behavior in simple lab-based tasks be extended to aid learning in educational contexts? And, if human beings are rational learners as most models assume, how do false beliefs arise and why are they so widespread?

The speakers consider answers to these questions that arise at the intersection of computer science, engineering, psychology, and education sciences. **Sen, Meng, Matthews, Alibali,** and **Zhu** consider how state of the art search techniques in machine learning, combined with cognitive models of human learning, can yield prescriptions for the optimal "diet" of practice in any given learning task. **Mason, Nowak,** and **Rau** describe research using a novel adaptive-sampling tool to measure the perceptual similarities discerned by undergraduates amongst diagrams of molecules, with the aim of understanding which perceptual features support or undermine a good understanding of the underlying chemical structure. **Binzak, Sievert, Murphy** and **Hubbard** apply contemporary multidimensional scaling algorithms to show that single digit number concepts differ qualitatively in experts and novices, and consider the implications for our developing understanding of numerical representation in the brain. Finally, **Frigo** and **Rogers** describe behavioral and simulation work suggesting a new hypothesis about how and why learning can go so wrong when information propagates in social networks.

Following these talks we will briefly lay out the challenges we have encountered in pursuing cross-disciplinary training of this kind with the goal of spurring a brief discussion session in which the audience can ask the program PIs and trainees about both the science and the training approach.

Optimizing Human Learning with Machine Teaching

A long-standing but elusive goal in machine-aided education has been to exploit cognitive models of human learning to select teaching or practice experiences for students that will efficiently lead them toward the desired knowledge state. We show how contemporary optimization methods allow theorists to discover, for any implemented learning model and desired outcome, an optimal teaching set—that is, a model training set that most efficiently produces the desired outcome given the model. We then report experiments assessing whether thus approach can be used to speed human learning, taking arithmetic as an example domain. Prior work has shown that people employ different learning strategies depending upon the structure of their practice experiences. When practice is purely symbolic (e.g. flash-card learning) people acquire item-specific knowledge that does not generalize, whereas when practice highlights underlying quantitative relationships, people learn functions that transfer well to unpracticed problems. This suggests that the optimal teaching set—the practice experiences that most rapidly produce knowledge that transfers broadly—will differ qualitatively depending on whether practice is symbolic or quantitative. We describe a series of experiments testing these predictions with participants learning new arithmetic relations through a computer-mediated teaching system that controls how practice problems are sampled. The results highlight the potential for machine teaching and cognitive modeling to boost learning in important educational domains.

Discovering perceived relations among molecular representations

To succeed in science courses, students must learn to rapidly and effortlessly translate among different visual representations of key representational structures with a high degree of fluency. This is a difficult task because students must learn to interpret individual representations on their own while simultaneously learning the relations among different representations. To better understand these processes, we used a novel adaptive embedding algorithm to identify which molecular representations beginning undergraduate students find similar and why (e.g., Lewis structure, ball-and-stick). Each trial of the embedding task asks participants to decide which of two candidate diagrams is most similar to a third. The algorithm adaptively selects triplets for comparison in a manner that allows for efficient estimation of perceived dissimilarities amongst all diagrams. From these dissimilarities we generated models of how different molecules are embedded in a perceptual similarity space, in the eyes of the typical undergraduate student. The result revealed an otherwise inaccessible set of visual features that jointly predict the novice similarity judgments, allowing us to identify the features salient to novice students without relying on verbal mediation. The same tool can likewise be used to identify features that govern the perceptual decisions of chemistry experts, with the ultimate aim of developing interventions that guide novice perceptual attention toward the features discerned by experts.

Beyond Magnitude: Psychological and Neural Representations of Number Properties

In classic work Roger Shepard and colleagues (1975) employed multidimensional scaling to show that, among the graduate students and colleagues who were his subjects, single-digit number concepts encode rich structure including primeness, parity, trinity, and exponentiation. This conclusion is hard to reconcile with much contemporary work suggesting that number concepts are grounded in an innate and widely-conserved approximate magnitude estimation system. In a series of studies, we used behavioral and brain imaging methods to investigate the psychological and neural mechanisms supporting adults' sensitivity to properties of number beyond magnitude, with the aim of reconciling this discrepancy. We first replicated Shepard's result in a cohort of students and colleagues, using a triadic judgment task to estimate conceptual similarities discerned amongst single-digit numbers. We then compared these representations among expert (math and CS grad students) and non-expert (Psychology undergraduates) groups, and found that rich structure was only observed in the experts. In a third study we examined whether explicit instruction can tune number concepts, with results revealing that magnitude information strongly dominates conceptual structure in non-experts but not experts. Finally, we have begun to assess what these behavioral differences suggest about the neural representation of number concepts. Participants viewed single-digit numbers while their brains were scanned in a slow event-related fMRI design. After a delay, they were instructed to think about a specific property of that number, and then were asked to judge whether that number matched a target number on that specific property. Using multivariate pattern classification, we assessed whether magnitude, primeness, and parity could be decoded from the neural responses measured, both before and after the important property was cued on each trial. The comparison of behavioral and brain imaging results carries important implications for an understanding of numerical cognition beyond magnitude, and for the role of expertise in reorganizing conceptual representations of numbers.

Why do false beliefs persist in crowds?

If human learning is rational as most cognitive models propose, what explains the emergence and widespread persistence of demonstrably false beliefs? We consider a new hypothesis that stems from an important difference between learning studies in the lab versus the real world. In the lab learners typically receive a single source of correct feedback, whereas in real life learners encounter many different sources of information that vary in their knowledge, motivation, and trustworthiness. How then do learners combine information from disagreeing sources? We examined how learners weight different sources when updating their beliefs, as a function of the degree to which the sources cohere with the learner's prior beliefs. The results reveal a previously undescribed learning bias that, counterintuitively, can lead groups of learners to disagree despite overwhelmingly similar learning experiences. To understand how this learning bias might lead to the emergence and persistence of false beliefs, we report simulation experiments in which many learners provide teaching labels to one another through a social network. Each simulated learner updates its beliefs in accordance with the empirically-observed learning bias, with the consequence that the cohort fractionates into mutually distrustful subgroups that adhere to different beliefs and ignore feedback from out-group members. The work thus provides a candidate mechanism for understanding how incorrect beliefs can arise and why they persist, even if individual learners behave in accordance with rational models in lab-based studies.

UW-Madison Participants

Computer Science: X. Zhu, A. Sen*

Educational Psychology: J. Binzak*, E. Hubbard, C. Kalish, P. Matthews, R. Meng*, M. Rau.

Electrical & Computer Engineering: B. Mason*, R. Nowak, S. Sievert*

Psychology: M. Alibali, V. Frigo*, A. Murphy*, T. Rogers

*LUCID Trainee